

Dense Supervision for Visual Comparisons via Synthetic Images

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Distinguishing subtle differences in attributes is valuable, yet learning to make visual comparisons remains non-trivial. Not only is the number of possible comparisons quadratic in the number of training images, but also access to images adequately spanning the space of fine-grained visual differences is limited. We propose to overcome the *sparsity of supervision* problem via synthetically generated images. Building on a state-of-the-art image generation engine, we sample pairs of training images exhibiting slight modifications of individual attributes. Augmenting real training image pairs with these examples, we then train attribute ranking models to predict the relative strength of an attribute in novel pairs of real images. Our results on datasets of faces and fashion images show the great promise of bootstrapping imperfect image generators to counteract sample sparsity for learning to rank.

INTRODUCTION

Fine-grained analysis of images often entails making *visual comparisons*. For example, given two products in a fashion catalog, a shopper may judge which shoe appears more pointy at the toe. Given two selfies, a teen may gauge in which one he is smiling more. Given two photos of houses for sale on a real estate website, a home buyer may analyze which facade looks better maintained. Given a series of MRI scans, a radiologist may judge which pair exhibits the most shape changes.

In these and many other such cases, we are interested in inferring how a pair of images compares in terms of a particular property, or “attribute”. That is, which is more *pointy*, *smiling*, *well-maintained*, etc. Importantly, the distinctions of interest are often quite subtle. Subtle comparisons arise both in image pairs that are very similar in almost every regard (e.g., two photos of the same individual wearing the same clothing, yet smiling more in one photo than the other), as well as image pairs that are holistically different yet exhibit only slight differences in the attribute in question (e.g., two individuals different in appearance, and one is smiling slightly more than the other).

A growing body of work explores computational models for visual comparisons [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12]. In particular, ranking models for “relative attributes” [2], [3], [4], [5], [9], [11] use human-ordered pairs of images to train a system to predict the relative ordering in novel image pairs.

A major challenge in training a ranking model is the *sparsity of supervision*. That sparsity stems from two factors: label availability and image availability. Because training instances consist of pairs of images—together with the ground truth human judgment about which exhibits the property more or less—the space of all possible comparisons is quadratic

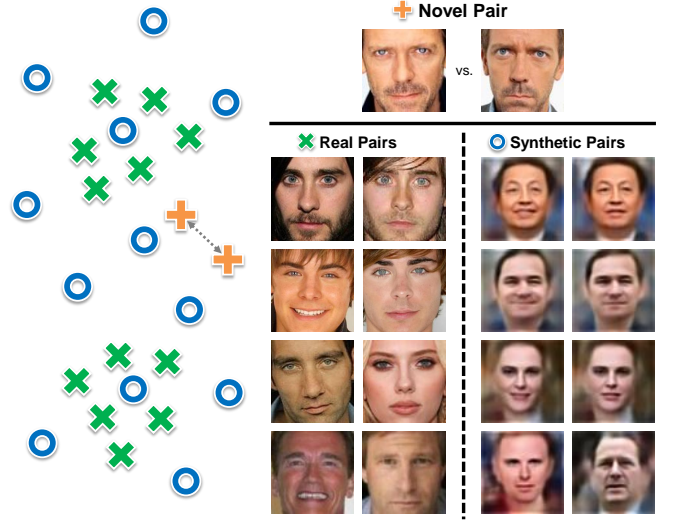


Fig. 1: Our method “densifies” supervision for training ranking functions to make visual comparisons, by generating ordered pairs of synthetic images. Here, when learning the attribute *smiling*, real training images need not be representative of the entire attribute space (e.g., Web photos may cluster around commonly photographed expressions, like toothy smiles). Our idea “fills in” the sparsely sampled regions to enable fine-grained supervision. Given a novel pair (top), the nearest synthetic pairs (right) may present better training data than the nearest real pairs (left).

in the number of potential training images. This quickly makes it intractable to label an image collection exhaustively for its comparative properties. At the same time, attribute comparisons entail a greater cognitive load than, for example, object category labeling. Indeed, the largest existing relative attribute datasets sample only less than 0.1% of all image pairs for ground truth labels [11], and there is a major size gap between standard datasets labeled for classification (now in the millions [13]) and those for comparisons (at best in the thousands [11]). A popular shortcut is to propagate category-level comparisons down to image instances [14], [4]—e.g., deem all ocean scenes as “more open” than all forest scenes—but this introduces substantial label noise and in practice underperforms training with instance-level comparisons [2].

Perhaps more insidious than the annotation cost, however, is the problem of even *curating* training images that sufficiently illustrate fine-grained differences. Critically, sparse supervision arises not simply because 1) we lack resources to get enough image pairs labeled, but also because 2) we lack a direct way to curate photos demonstrating all sorts of subtle attribute changes. For example, how might we gather unlabeled image pairs depicting all subtle differences in “sportiness” in clothing images or “surprisedness” in faces?

As a result, even today’s best datasets contain only partial representations of an attribute. See Figure 1.

We propose to use *synthetic image pairs* to overcome the sparsity of supervision problem when learning to compare images. The main idea is to synthesize plausible photos exhibiting variations along a given attribute from a generative model, thereby recovering samples in regions of the attribute space that are underrepresented among the real training images. After (optionally) verifying the comparative labels with human annotators, we train a discriminative ranking model using the synthetic training pairs in conjunction with real image pairs. The resulting model predicts attribute comparisons between novel pairs of real images.

Our idea can be seen as semantic “jittering” of the data to augment real image training sets with nearby variations. The systemic perturbation of images through label-preserving transforms like mirroring/scaling is now common practice in training deep networks for classification [15], [16], [17]. Whereas such low-level image manipulations are performed independent of the semantic content of the training instance, the variations introduced by our approach are high-level changes that affect the very meaning of the image, e.g., facial shape changes as the expression changes. In other words, our jitter has a semantic basis rather than a purely geometric/photometric basis. See Figure 2.

We demonstrate our approach in domains where subtle visual comparisons are often relevant: faces and fashion. To support our experiments, we use crowdsourcing to establish a lexicon of fine-grained attributes that people naturally use to describe subtle differences, and we gather new comparison annotations. In both domains, by artificially “densifying” comparative supervision, we show promising results for precise attribute predictions.

RELATED WORK

Attribute Comparisons: Since the introduction of relative attributes [4], the task of attribute comparisons has gained attention for its variety of applications, such as online shopping [2], biometrics [18], novel forms of low-supervision learning [14], [6], and font selection [19].

The original approach [4] adopts a learning-to-rank framework [20]. Pairwise supervision is used to train a linear ranking function for each attribute. More recently, non-linear ranking functions [3], combining feature-specific rankers [1], and training local rankers on the fly [11], [12] are all promising ways to improve accuracy. Other work investigates features tailored for attribute comparisons, such as facial landmark detectors to identify discriminative local parts [5] and *visual chains* to discover relevant parts even when they change in appearance across the spectrum of the attribute [9]. The success of deep networks has motivated end-to-end frameworks for learning features and attribute ranking functions simultaneously [7], [8], [10]. Unlike any of the above, the novelty of our idea rests in the source data for training, not the learning algorithm. Thus, our method stands to benefit any such existing learning framework, and can be used without modification.

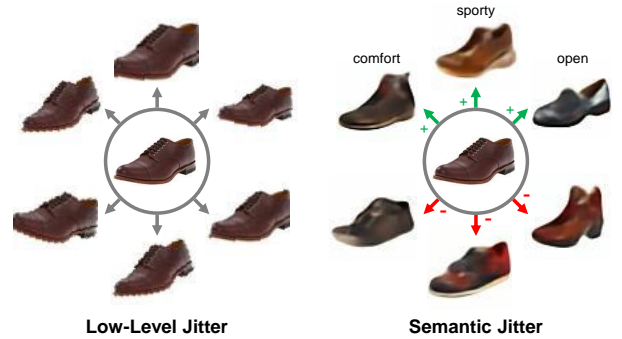


Fig. 2: Whereas standard data augmentation with low-level “jitter” (left) expands training data with image-space alterations (mirroring, scaling, etc.), our *semantic jitter* (right) expands training data with high-level alterations, tweaking semantic properties in a controlled manner. Best viewed in color.

Attributes and Image Synthesis: Our approach relies on a generative model for image synthesis that can progressively modify a target attribute. Attribute-specific alterations have been considered in several recent methods, primarily for face images. Some target a specific domain and attribute, such as methods to enhance the “memorability” [21] or age [22] of facial photos, or to edit outdoor scenes with transient attributes like weather [23]. Alternatively, the success of deep neural networks for image generation (i.e., Generative Adversarial Nets (GAN) [24] or Variational Auto-Encoders (VAE) [25], [26], [27]) opens the door to learning how to generate images conditioned on desired properties [28], [29], [30], [31], [32]. For example, a conditional multimodal auto-encoder can generate faces from attribute descriptions [30], and focus on identity-preserving changes [29]. We employ the state-of-the-art model of [31] due to its generality. Whereas the above methods aim to produce an image for human inspection, we aim to generate dense supervision for learning algorithms.

Training Recognition Models with Synthetic Images: The use of synthetic images as training data has been explored to a limited extent, primarily for human bodies. Taking advantage of high quality graphics models for humanoids, researchers use rendered images of people from various viewpoints and body poses to train pose estimation systems [33], [34] or person detectors [35]. For objects beyond people, recent work considers how to exploit non-photorealistic images generated from 3D CAD models to augment training sets for object detection [36], or words rendered in different fonts for text recognition [37].

While these methods share our concern about the sparsity of supervision, our focus on attributes and ranking is unique. Furthermore, existing methods work with images rendered with a graphics engine from complete 3D models with directly tuneable parameters (body pose, camera viewpoint, etc.). In contrast, we investigate images generated from a 2D image synthesis engine in which the modes of variation are controlled by a learned model. Thus, our formulation offers wider applicability (beyond tasks for which one has a 3D model in hand, and beyond variability in camera pose and lighting parameters).

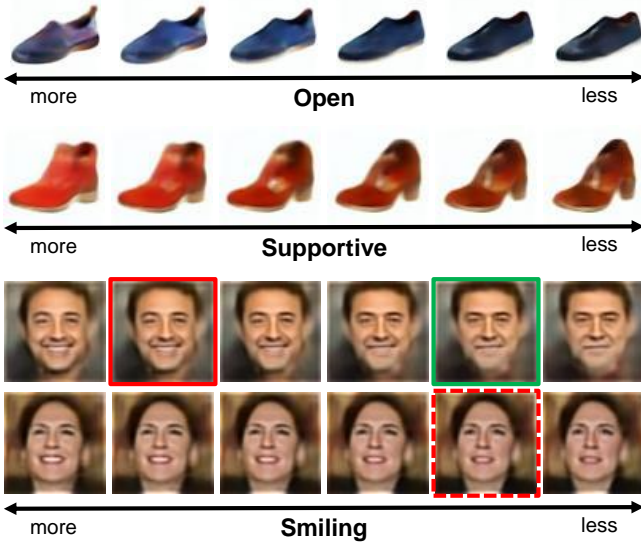


Fig. 3: Spectra of generated images given an identity and an attribute. We form two types of image pairs: The two solid boxes represent an *intra-identity pair*, whereas the two red boxes represent an *inter-identity pair*.

APPROACH

Our idea is to “densify” supervision for learning to make visual comparisons, by leveraging images sampled from an attribute-conditioned generative model. First we overview the visual comparison task and baseline model. Then, we describe the generative model and how we elicit dense supervision pairs from it. Finally, we integrate both synthetic and real images to train a ranker suited for fine-grained attribute comparisons.

Visual Comparison Predictor

Let $\mathbf{x}_i \in \mathbb{R}^{N_x}$ denote an image with N_x pixels and let $\phi(\mathbf{x}_i) \in \mathbb{R}^D$ denote its D -dimensional descriptor (e.g., Gist, color, CNN feature, etc.). Given a target attribute \mathcal{A} and two images \mathbf{x}_i and \mathbf{x}_j , the goal of visual comparison is to determine which of the images contains “more” of the specified attribute.

Relative attributes [4] offer a learning-to-rank solution for computing such comparisons based on the SVM-Rank framework [20]. Using ordered pairs of images $\mathcal{P}_{\mathcal{A}} = \{(\mathbf{x}_i, \mathbf{x}_j)\}$ for which humans perceive image i to have the attribute \mathcal{A} more than image j , the idea is to learn a ranking function $R_{\mathcal{A}}(\phi(\mathbf{x}))$ that satisfies as many of the specified orderings as possible. In the linear case,

$$R_{\mathcal{A}}(\phi(\mathbf{x})) = \mathbf{w}_{\mathcal{A}}^T \phi(\mathbf{x}) \quad (1)$$

$$\forall (i, j) \in \mathcal{P}_{\mathcal{A}} : R_{\mathcal{A}}(\phi(\mathbf{x}_i)) > R_{\mathcal{A}}(\phi(\mathbf{x}_j)),$$

where \mathbf{w} is the ranking model parameters (weight vector) optimized in training. The optimal \mathbf{w} maximizes the rank margin between “more” and “less” training pairs and satisfies the given orderings, subject to slack variable penalties. The formulation of [20] is kernelizable, which allows extension to non-linear ranking functions.

Given a novel image pair $(\mathbf{x}_m, \mathbf{x}_n)$, the ranker compares them to determine which exhibits the attribute more. If

$R_{\mathcal{A}}(\phi(\mathbf{x}_m)) > R_{\mathcal{A}}(\phi(\mathbf{x}_n))$, then image m exhibits attribute \mathcal{A} more than image n , and vice versa.

Our goal is to address the sparsity issue in $\mathcal{P}_{\mathcal{A}}$ through the addition of synthetic image pairs, such that the training pairs are more representative of subtle differences in \mathcal{A} . We build on this attribute ranking model due to its simplicity of training and good results in the literature [14], [2], [4], [11], [12]. However, our approach does not interfere with the formulation of the specific comparison model used. So, improvements in densifying supervision are orthogonal to improvements in the relative attribute prediction model. Alternative ranking methods (e.g., Siamese embeddings and others mentioned in related work) could also benefit from our work.

Synthesizing Dense Supervision

The key to improving *coverage* in the attribute space is the ability to generate images exhibiting subtle differences—with respect to the given attribute—while keeping the others aspects constant. In other words, we want to walk semantically in the high-level attribute space.

Attribute-Conditioned Image Generator

We adopt an existing state-of-the-art image generation system, Attribute2Image, recently introduced by Yan et al. [31], [32], which can generate images that exhibit a given set of attributes and latent factors.

Suppose we have a lexicon of N_a attributes, $\{\mathcal{A}_1, \dots, \mathcal{A}_{N_a}\}$. Let $\mathbf{y} \in \mathbb{R}^{N_a}$ be a vector containing the strength of each attribute, and let $\mathbf{z} \in \mathbb{R}^{N_z}$ be the latent variables. The Attribute2Image approach constructs a generative model for

$$p_{\theta}(\mathbf{x}|\mathbf{y}, \mathbf{z}) \quad (2)$$

that produces realistic images $\mathbf{x} \in \mathbb{R}^{N_x}$ conditioned on \mathbf{y} and \mathbf{z} . The authors maximize the variational lower bound of the log-likelihood $\log p_{\theta}(\mathbf{x}|\mathbf{y})$ in order to obtain the model parameters θ . The model is implemented with a Conditional Variational Auto-Encoder (CVAE). The network architecture generates the entangled hidden representation of the attributes and latent factors with multilayer perceptrons, then generates the image pixels with a coarse-to-fine convolutional decoder. The authors apply their approach for attribute progression, image completion, and image retrieval. See [31], [32] for more details.

Generating Dense Synthetic Image Pairs

We propose to leverage the Attribute2Image [31] engine to supply realistic synthetic training images that “fill in” under-represented regions of image space, which we show helps train a model to estimate fine-grained attribute comparisons.

The next key step is to generate a series of synthetic *identities*, then sample images for those identities that are close by in a desired semantic attribute space.¹ The resulting images will comprise a set of synthetic image pairs $\mathcal{S}_{\mathcal{A}}$. The orderings

¹Note that here the word identity means an instance for some domain, not necessarily a human identity; in experiments we apply our idea both for human faces as well as fashion images of shoes.

of those pairs will be verified by human annotators before augmenting the real-image training data \mathcal{P}_A for attribute \mathcal{A} . The next section describes how we use the hybrid real and synthetic image pairs to train an attribute predictor.

Each identity is defined by an entangled set of latent factors and attributes. Let $p(\mathbf{y})$ denote a prior over the attribute occurrences in the domain of interest. We model this prior with a multivariate Gaussian whose mean and covariance are learned from the attribute strengths observed in real training images: $p(\mathbf{y}) = \mathcal{N}(\mu, \Sigma)$. This distribution captures the joint interactions between attributes, such that a sample from the prior reflects the co-occurrence behavior of different pairs of attributes (e.g., shoes that are very pointy are often also uncomfortable, faces that have facial hair are often masculine, etc.).² The prior over latent factors $p(\mathbf{z})$, captures all non-attribute properties like pose, background, and illumination. Following [32], we represent $p(\mathbf{z})$ with an isotropic multivariate Gaussian.

To sample an identity

$$\mathcal{I}_j = (\mathbf{y}_j, \mathbf{z}_j) \quad (3)$$

we sample \mathbf{y}_j and \mathbf{z}_j from their respective priors. Then, using an Attribute2Image model trained for the domain of interest, we sample from $p_\theta(\mathbf{x}|\mathbf{y}_j, \mathbf{z}_j)$ to generate an image $\hat{\mathbf{x}}_j \in \mathbb{R}^{N_x}$ for this identity. Alternatively, we could sample an identity from a single real image, after inferring its latent variables through the generative model [10]. However, doing so requires having access to attribute labels for that image. More importantly, sampling novel identities from the prior (vs. an individual image) further supports our goal to densify supervision, since we can draw nearby instances that need not have been exactly observed in the real training images. In experiments, we generate thousands of identities.

Next we modify the strength of a single attribute in \mathbf{y} while keeping all other variables constant. This yields two “tweaked” identities $\mathcal{I}_j^{(-)}$ and $\mathcal{I}_j^{(+)}$ that look much like \mathcal{I}_j , only with a bit less or more of the attribute, respectively. Specifically, let σ_A denote the standard deviation of attribute scores observed in real training images for attribute \mathcal{A} . We revise the attribute vector for identity \mathcal{I}_j by replacing the dimension for attribute \mathcal{A} according to

$$\begin{aligned} \mathbf{y}_j^{(-)}(\mathcal{A}) &= \mathbf{y}_j(\mathcal{A}) - 2\sigma_A \text{ and} \\ \mathbf{y}_j^{(+)}(\mathcal{A}) &= \mathbf{y}_j(\mathcal{A}) + 2\sigma_A, \end{aligned} \quad (4)$$

and $\mathbf{y}_j^{(-)}(a) = \mathbf{y}_j^{(+)}(a) = \mathbf{y}_j(a), \forall a \neq \mathcal{A}$. Finally, we sample from $p_\theta(\mathbf{x}|\mathbf{y}_j^{(-)}, \mathbf{z}_j)$ and $p_\theta(\mathbf{x}|\mathbf{y}_j^{(+)}, \mathbf{z}_j)$ to obtain images $\hat{\mathbf{x}}_j^{(-)}$ and $\hat{\mathbf{x}}_j^{(+)}$.

Figure 3 shows examples of synthetic images generated for a sampled identity, varying only in one attribute. The generated images form a smooth progression in the attribute space. This is exactly what allows us to curate fine-grained pairs of images

that are very similar in attribute strength. Crucially, such pairs are rarely possible to curate systematically among real images. The exception is special “hands-on” scenarios, e.g., for faces, asking subjects in a lab to slowly exhibit different facial expressions, or systematically varying lighting or head pose (cf. PIE, Yale face datasets). The hands-on protocol is not only expensive, it is inapplicable in most domains outside of faces and for rich attribute vocabularies. For example, how would one physically modify the pointiness of a shoe’s toe, while leaving all other properties the same? Furthermore, the generation process allows us to collect in a controlled manner subtle visual changes *across* identities as well.

Next we pair up the synthetic images to form the set \mathcal{S}_A , which, once verified and pruned by human annotators, will augment the real training image pairs \mathcal{P}_A . In order to maximize our coverage of the attribute space, we sample two types of synthetic image pairs: *intra-identity pairs*, which are images sampled from the same identity’s spectrum and *inter-identity pairs*, which are images sampled from different spectrums (see Fig. 3). Specifically, for every identity j , \mathcal{S}_A receives intra pairs $\{(\hat{\mathbf{x}}_j^{(-)}, \hat{\mathbf{x}}_j), (\hat{\mathbf{x}}_j, \hat{\mathbf{x}}_j^{(+)})\}$ and for every pair of identities (j, k) , \mathcal{S}_A receives inter pairs $\{(\hat{\mathbf{x}}_j, \hat{\mathbf{x}}_k^{(+)})\}, (\hat{\mathbf{x}}_k^{(-)}, \hat{\mathbf{x}}_j)\}$.

We expect many of the generated pairs to be valid, meaning that both images are realistic human interpretable images and that the pair exhibits a slight difference in the attribute of interest. However, this need not always be true. In some cases the generator will create images that do not appear to manipulate the attribute of interest, or where the pair is close enough in the attribute to be indistinguishable, or where the images simply do not look realistic enough to tell. (Our experiments indicate this happens about 15% of the time.) Hence, to avoid label noise, once the synthetic pairs are generated, we collect pairwise supervision from 5 human crowdworkers per pair. In experiments we test whether the ordering produced by the generative model could be used without any human verification.

Local Learning with Hybrid Comparisons

While in principle any learning algorithm for visual comparisons could exploit the newly generated synthetic image pairs, we expect them to be particularly powerful for *local learning* models. In local learning, one trains a model using only those labeled instances that are nearest to the test input [38], [39]. The advantage of local learning is accounting for neighborhood statistics of the data; a low-capacity model can succeed because it focuses on relevant instances. Just as bare bones nearest neighbors relies on adequate density of labeled exemplars to succeed, in general local learning can be expected to flourish when the space of training examples is more densely populated.

Thus, inspired by its success in recent work for attributes [11], we employ a local learning model. Rather than use all available image pairs for training, the idea is to train a local model for each novel image pair (at test time) using only the most relevant image pairs. Here relevance is captured by the distance between *pairs* of images: for a test pair $(\mathbf{x}_p, \mathbf{x}_q)$, one gathers the K nearest pairs according to the product of

²Note that this prior is nonetheless assumed to be coarse, since a subset of dimensions in \mathbf{y} consist of the very attributes we wish to learn better via densifying supervision. For the sake of the prior, the training image attribute strengths originate from the raw decision outputs of a preliminary binary attribute classifier trained on disjoint data labeled for the presence/absence of the attribute (see experiments).

element-wise distances between (x_p, x_q) and each training pair, using the minimum over both orderings of (x_p, x_q) to account for its elements’ yet unknown relative attribute strengths. Only those K pairs are used to train a ranking function to predict the order of (x_p, x_q) . See [11] for details.

Given a hybrid set of sparse real pairs and dense synthetic pairs, $\{\mathcal{P}_A \cup \mathcal{S}_A\}$, we use a local model to select the most relevant mix of real and synthetic pairs. The local model reinforces our hypothesis that data *density* is at least as important as data *quantity* for learning subtle visual comparisons. See Figure 1.

A natural question to ask is why not feed back the synthetic image pairs into the same generative model that produced them, to try and enhance its training? We avoid doing so for two important reasons. First, this would lead to a circularity bias where the system would essentially be trying to exploit new data that it has already learned to capture well (and hence could generate already). Second, the particular image generator we employ is not equipped to learn from relative supervision nor make relative *comparisons* on novel data. Rather, it learns from individual images with absolute attribute strengths. Thus, we use the synthetic data to train a distinct model capable of learning relative visual concepts.

A LEXICON OF FINE-GRAINED ATTRIBUTES

As a secondary contribution, we construct a new fine-grained relative attributes dataset. As discussed in the introduction, label sparsity is as much of an issue in visual comparison as sample sparsity. While there are numerous large image datasets for single image tasks such as object detection, datasets for visual comparison with *instance-level pairwise supervision* are more modest. In addition, the *lexicon* of attributes used in existing relative attributes datasets are selected based on the authors’ intuitions, i.e., in terms of words that seem domain relevant [2] or words that seem to exhibit the most subtle fine-grained differences [11].

Towards addressing both limitations, we 1) use crowdsourcing to mine for an attribute lexicon that is explicitly fine-grained, and 2) collect a large number of pairwise orderings for each attribute in that lexicon. We focus on fashion images of shoes, leveraging images from the UT-Zap50K shoe dataset [11].

Given a pair of images, we ask Amazon MTurk workers to complete the sentence, “Shoe A is a *little more* (insert word) than Shoe B” using a single word. They are instructed to identify subtle differences between the images and provide a short rationale to explain their choices. The goal is to find out how people differentiate fine-grained differences between shoe images. Over 1,000 workers participated in the study, yielding a total of 350+ distinct word suggestions across 4,000 image pairs viewed. This approach to lexicon generation takes inspiration from the strategy of [40], but fine-tuned towards requesting those “almost indistinguishably” visual changes rather than arbitrary attribute differences.

We post-process the word results through evaluation of the rationales and merging of synonyms. Figure 4 shows a word cloud of the raw results. Finally, we select the 10

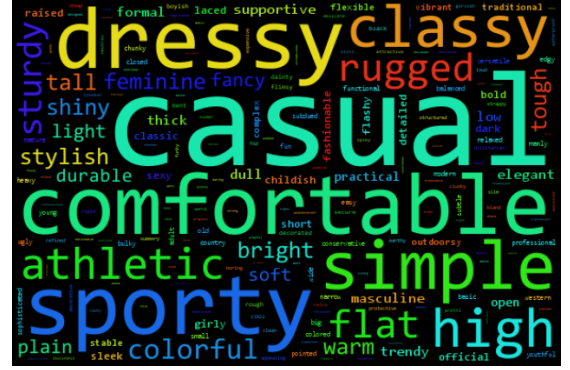


Fig. 4: Word cloud depicting our crowd-mined data for a fine-grained relative attribute lexicon for shoes (before post-processing).

most frequently appearing words as the new **fine-grained relative attribute lexicon** for shoes: *comfort*, *casual*, *simple*, *sporty*, *colorful*, *durable*, *supportive*, *bold*, *sleek*, and *open*. See appendix for more details.

Using this new lexicon, we collect pairwise supervision for about 4,000 pairs for each of the 10 attributes, using images from UT-Zap50K. This is a step towards denser supervision on real images—more than three times the comparison labels provided in the original dataset.³ Still, as we will see in results, the greater density offered by synthetic training instances is needed for best results.

EXPERIMENTS

We conduct fine-grained visual comparison experiments to validate the benefit of our dense supervision idea.

Datasets Our experiments rely on the following existing and newly collected datasets:

Zap50K+New Lexicon: The UT-Zap50K dataset [11] consists of 50,025 catalog shoe images taken from Zappos.com. It contains 2,800 pairwise labels on average for each of 4 relative attributes: *open*, *pointy*, *sporty*, and *comfort*. The labels are divided into coarse pairs (UT-Zap50K-1) and fine-grained pairs (UT-Zap50K-2). We augment it with the crowd-mined lexicon for 10 additional attributes.

Zap50K-Synth: A new synthetic shoe dataset with pairwise labels on the new 10-attribute lexicon. We train the generative model using a subset of UT-Zap50K images and a superset of the above attributes (see appendix for details). We generate 1,000 identities and each one is used to sample both an intra- and inter-identity pair, yielding roughly 2,000 pairwise labels per attribute. The synthetic images are 64×64 pixels.

LFW-10: The LFW-10 dataset [5] consists of 2,000 face images taken from Labeled Faces in the Wild (LFW) [41]. It contains roughly 1,000 pairwise labels on each of the 10 relative attributes: *bald*, *dark hair*, *eyes open*, *good looking*, *masculine*, *mouth open*, *smile*, *visible teeth*, *visible forehead*, and *young*. After pruning the low quality pairs with less than

³See appendix for details, including how samples were selected for labeling and the interface.

	Comfort	Casual	Simple	Sporty	Colorful	Durable	Supportive	Bold	Sleek	Open	Mean
Real	84.03	86.11	86.89	87.27	83.84	85.15	87.75	83.71	86.06	84.41	85.52
Jitter	84.49	87.35	88.52	83.36	85.36	86.77	86.86	85.36	86.31	82.53	85.99
DenseSynth-Auto	84.72	87.35	87.59	86.06	85.74	86.78	83.74	85.36	86.55	83.87	85.78
DenseSynth (Ours)	86.11	87.35	89.46	89.09	86.31	86.54	87.08	88.45	87.53	86.24	87.42

TABLE I: Results on Zap50K for the new lexicon of 10 attributes most frequently used to distinguish fine-grained differences between shoe images.

80% agreement from the workers, there are 270 pairwise labels on average per attribute.

PFSmile: A new dataset consisting of 64 face images from the Public Figures face dataset (PubFigAttr) [42], [4]. 8 frontal images of 8 random individuals are selected, with the frontal images showing different degrees of *smilingness* for the given individual (e.g. images of Zach Efron going from not smiling at all to fully smiling). While we would have liked more PubFig face attributes, we found that smiling is the only attribute from PubFigAttr that manifests fine-grained changes on the same individuals. This reinforces our concern about the difficulty of manually curating images with subtle attribute differences for learning—despite the fact that such differences exist in real-life daily experience. We collect fine-grained supervision on all possible pairwise comparisons among images of the same individual. After pruning, there are 211 pairwise labels.

LFW-Synth: A new synthetic face dataset with pairwise labels on the attribute *smiling* (the only attribute overlapping between LFW-10 and PFSmile). We train the generative model on a subset of LFW images and the 73 attributes from [42], [31]. We generate 2,000 identities and sample a total of 4,000 intra pairs and 1,000 inter pairs. The synthetic images are 35×35 pixels, after zooming to a tight bounding box around the face region.

To our knowledge there exist no other instance-labeled relative attribute datasets.

Implementation Details For image features ϕ , we use Gist [43] and 30-bin Lab color histograms, following [4], [11]. We also tested CNN features from pre-trained models, but, similar to recent reports in attribute work [8], we found them inferior. This is likely due to the domain shift from ImageNet to the catalog images in UT-Zap50K and zoomed in face images in LFW, respectively. Early experiments showed that a mix of inter and intra-identity pairs was most effective, so we used a 50-50 mix in all experiments. We resize real images to match the resolution of the synthetic ones for both datasets. We use code kindly shared by the authors for the Attribute2Image system [31], with all default parameters including the prior on z .

We stress that the images used for training the generative model, for training the ranking functions, and for evaluating (test set) *are kept strictly disjoint at all times*.

Baselines We compare the following methods:

- **Real:** Training pool consists of only real image pairs, labeled by human annotators.
- **DenseSynth (Ours):** Training pool consists of the same real image pairs as Real, augmented with our densely

	Open	Sporty	Comfort	Mean
LP [11]	88.53	92.20	90.90	90.54
LP+Jitter	88.97	92.63	90.07	90.56
LP+DenseSynth-Auto	87.43	90.87	91.33	89.88
LP+DenseSynth (Ours)	88.63	92.53	91.33	90.83

TABLE II: Results on UT-Zap50K-1 (coarse pairs).

	Open	Sporty	Comfort	Mean
LP [11]	71.64	61.22	59.75	64.20
LP+Jitter	68.64	65.74	61.90	65.43
LP+DenseSynth-Auto	68.64	63.62	63.23	65.16
LP+DenseSynth (Ours)	71.27	67.13	64.24	67.55

TABLE III: Results on UT-Zap50K-2 (fine-grained pairs).

supervised synthetic image pairs.

- **DenseSynth-Auto:** Ablated version of ours, where the pairwise supervision for synthetic images pairs is obtained automatically based on the absolute attribute strength used to generate the respective images.
- **Jitter:** Uses the same real training pairs, but augments them with pairs using traditional low-level jitter. Each real image is jittered following parameters in [15] in a combination of five changes: translation, scaling, rotation, contrast, and color. A jittered pair inherits the corresponding real pair’s label.
- **Yu et al. Local Pairs (LP)** [11]: An existing method that uses local learning for fine-grained attribute comparisons, trained with only real images.

We run experiments on two models: *global*, where the linear SVM-Rank model from [4] is trained on all available labeled pairs, and *local*, where the ranker is trained with only the test pair’s K neighbor pairs [11]. K is validated per method on held-out data. Since the local models are consistently better than the global ones (for our approach and the baselines), for clarity we report the local ones here and the global ones below in the appendix.

Experiment 1: Fashion Images of Shoes

Fashion product images offer a great testbed for fine-grained comparisons. This experiment uses UT-Zap50K for real training and testing pairs, and UT-Zap50K-Synth for synthetic training pairs. There are 10 attributes total. Since the real train and test pairs come from the same dataset, this presents a challenge for our approach—can synthetic images, despite their inherent domain shift, still help the algorithm learn a more reliable model?

Table VII shows the results. Our approach outperforms all baselines, demonstrating the strength of our dense synthetic pairs. Augmenting with traditional low-level jitter also provides a slight boost in performance, but not as much as ours. Looking at the composition of the local neighbors, we see that

	Real	Jitter	DenseSynth-Auto	DenseSynth (Ours)
Smiling	69.29	74.29	75.00	76.43

TABLE IV: Results on PFSmile for the attribute *smiling*.

	Shoes	Faces
Real	83.29	89.67
DenseSynth	89.29	97.67

TABLE V: Results on human-labeled synthetic test pairs for both domains.

about 85% of the selected local neighbors are our synthetic pairs (15% real) while only 55% are jittered pairs (45% real). Thus, our synthetic pairs are indeed heavily influencing the learning of the ranking models. We conclude that semantic jitter densifies the space more effectively than low-level jitter.

Figure 5 shows examples of nearest neighbor image pairs retrieved for some sample novel test pairs for various attributes in both datasets. These examples illustrate how 1) the synthetic images densify the supervision, providing perceptually closer instances for training, and 2) that both real and synthetic image pairs are playing an important role in the local learning algorithm.

Next, we evaluate our method’s influence on an existing method from the literature. We follow the experimental setup in [11] for the “LocalPair” method, then augment the system with our dense synthetic pairs. Note that we omit the metric learning (FG) step, since we lack the “similar” labels on synthetic data needed to train it. We train the generative model using all images from UT-Zap50K that do not appear in UT-Zap50K-1 and UT-Zap50K-2. We test all three attributes that overlap between the existing UT-Zap50K four and our 10 collected ones: *open*, *sporty*, and *comfort*. We do *not* leverage the newly collected real labeled data for our method here, to avoid an unfair advantage.

Tables II and III benchmark our result against the reported results [11] and the Jitter baseline. Overall, our dense synthetic pairs improve upon both the existing LocalPair [11] result as well as LocalPair augmented with Jitter. The gain is most significant in the more challenging fine-grained case (Table III), with absolute gains averaging 3 points—and up to 6 points on *sporty*. This makes sense: sparse real training images are (nearly) enough for the easier case where test pairs show an obvious attribute difference (UT-Zap50K-1), but clearly insufficient for subtle cases (UT-Zap50K-2).

Overall, our gain is significant, considering it is achieved without any changes to the model, the features, or the experimental setup. In addition, our system is restricted to scaled down 64×64 images (for our real and synthetic images) as opposed to the 150×100 real images used in [11].

Experiment 2: Human Faces

Next we consider the face domain, where fine-grained comparisons are also of great practical interest. This experiment uses LFW-10 for real training pairs, LFW-Synth for synthetic training pairs, and PFSmile for real testing pairs. Here we have a domain shift, since the real train and test images are from different datasets with somewhat different properties. Since PFSmile only contains image pairs of the same individual, the comparison task is fine-grained by design.

Table VIII shows the results. Consistent with the above result, our approach outperforms all baselines. Interestingly, if we forgo human verification of our synthetic pairs, we still obtain a decent gain over the baseline: 75.00% vs. 69.29%. That amounts to a relative gain of 8% over the status quo of training with real images alone, with no additional human supervision. However, there is enough noise in the orderings that human annotation effort, if available, is worth applying to the synthetic data for best results. Future directions could explore ways to minimize the effort to only the most questionable pairs, in order to augment the real pairs with a mix of automatically generated and human generated comparisons. See Figure 5 for example neighboring pairs.

Experiment 3: Synthetic Test Images

Finally, we consider test sets for both datasets comprised of 300 novel synthetic image pairs drawn from 1,000 identities. The ordering labels are human verified for all test image pairs. Table V shows the results (see appendix for per-attribute scores on Shoes). Our gains here are substantial, e.g., an 8 point absolute gain for *smiling*. Admittedly, our method has the advantage here of learning on data from the same domain (namely, synthetic images generated from Attribute2Image), whereas the Real baseline has to overcome this domain shift to generalize. However, our method overcomes this very same domain shift in the other direction in all of the results reported above on real test image pairs.

CONCLUSION

Supervision sparsity hurts fine-grained attributes—closely related image pairs are exactly the ones the system must learn from. We presented a new approach to training data augmentation, in which real training data mixes with realistic synthetic examples that vary slightly in their high-level attributes. The novel generated training images more densely sample the space of images to illustrate fine-grained attribute differences. We stress that sample *density* is distinct from sample *quantity*. Simply gathering more real images cannot offer the same fine-grained density, due to the curation problem. Preliminary results suggest there is potential to apply our approach without human verification of the labels, which could eventually help address label sparsity issue as well.

Acknowledgements We thank Xinchun Yan and Honglak Lee for helpful discussions and for sharing the original code for the Attribute2Image engine.

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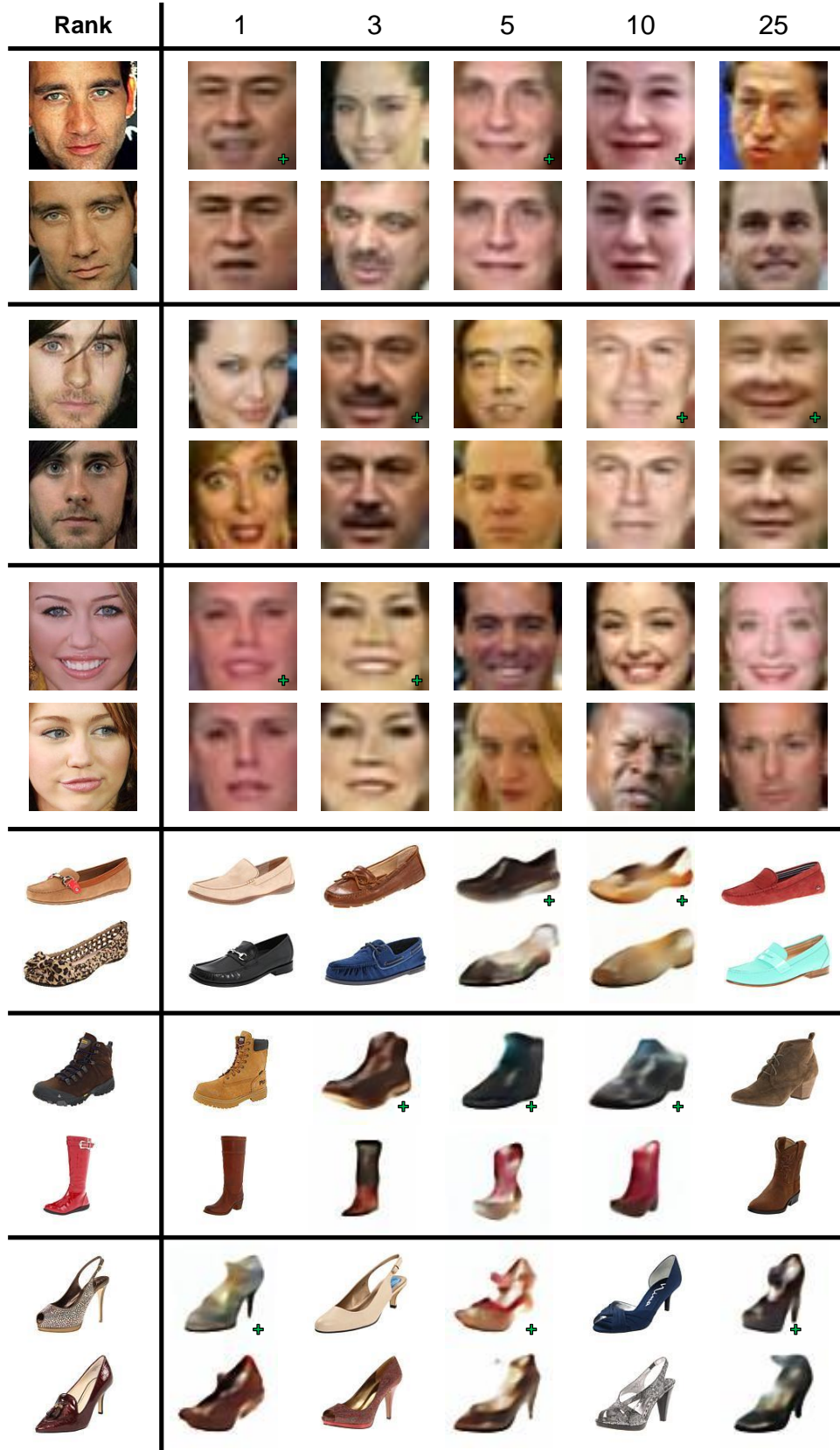


Fig. 5: Examples of nearest neighbor image pairs given novel test pairs (left). Both real and synthetic image pairs appear in the top neighbors, demonstrating their combined importance in the local learning algorithm. A green plus sign denotes a synthetic image pair.

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	Comfort	Casual	Simple	Sporty	Colorful	Durable	Supportive	Bold	Sleek	Open	Mean
Real	86.34	81.77	78.46	82.51	90.05	99.55	68.77	79.70	92.45	73.28	83.29
DenseSynth	95.03	85.42	81.03	84.75	96.99	100.00	84.19	86.09	96.77	82.59	89.29

TABLE VI: Per-attribute results on human-labeled synthetic test pairs for Zap50K using local models.

	Comfort	Casual	Simple	Sporty	Colorful	Durable	Supportive	Bold	Sleek	Open	Mean
Real	84.03	86.11	86.89	87.27	83.84	85.15	87.75	83.71	86.06	84.41	85.52
Real-G	83.80	88.89	86.65	83.36	88.02	84.24	85.52	84.74	87.29	81.99	85.45
Jitter	84.49	87.35	88.52	83.36	85.36	86.77	86.86	85.36	86.31	82.53	85.99
Jitter-G	84.72	83.69	86.22	85.15	87.45	84.69	89.53	84.33	83.90	81.99	85.17
DenseSynth-Auto	84.72	87.35	87.59	86.06	85.74	86.78	83.74	85.36	86.55	83.87	85.78
DenseSynth-Auto-G	84.26	85.85	85.28	87.27	87.26	83.06	87.97	85.77	84.88	79.03	85.06
DenseSynth (Ours)	86.11	87.35	89.46	89.09	86.31	86.54	87.08	88.45	87.53	86.24	87.42
DenseSynth-G	85.19	86.77	85.98	88.18	87.83	83.76	88.42	86.19	85.61	80.38	85.83

TABLE VII: Comprehensive results of all baselines on Zap50K for the new lexicon of 10 relative attributes. “G” denotes the use of a global ranking model instead of a local ranking model.

APPENDIX

Fine-Grained Attribute Lexicon

We use the UT-Zap50K shoe dataset [11] to perform our lexical study. It contains 50,025 catalog shoe images along with a set of meta-data that are associated with each image. Our goal is to study how humans distinguish fine-grained differences in similar images. Specifically, we want to know what words humans use to describe fine-grained differences.

Experimental Design We design our experiments in the form of “complete the sentence” questions and test them on the Amazon MTurk workers. We experiment with two kinds of designs: Design 1 compares two individual images while Design 2 compares one image against a group of six images. Given the meta-data which contains a category (i.e. slippers, boots) and subcategory (i.e. flats, ankle high) labels for each image, we combine these labels into a set of 21 unique category-subcategory pseudo-classes. Using these new pseudo-classes, we sample 4,000 supervision pairs (for each design) where 80% are comparing within the same pseudo-class and 20% are comparing within the same category. By focusing sampled pairs among items within a pseudo-class, we aim for a majority of the pairs to contain visually quite related items, thus forcing the human subjects to zero in on fine-grained differences.

For each question, the workers are asked to complete the sentence, “Shoe A is a *little more/less* (insert word) than Shoe B” using a single word (“Shoe B” is replaced by “Group B” for Design 2). They are instructed to identify **subtle differences** between the images and provide a short rationale to elaborate on their choices. Figure 6 shows a screenshot of a sample question.

Post-Processing We post-process the fine-grained word suggestions through correcting for human variations (i.e. misspelling, word forms), merging of visual synonyms/antonyms, and evaluation of the rationales. For example, “casual” and “formal” are visual antonyms and workers used similar keywords in their rationales for “durable” and “rugged”. In both cases, the frequency counts for the two words are combined. Over 1,000 MTurk workers participated in our study, yielding

Smiling	Local	Global
Real	69.29	72.05
Jitter	74.29	71.43
DenseSynth-Auto	75.00	76.43
DenseSynth (Ours)	76.43	77.86

TABLE VIII: Comprehensive results for all baselines on PFSmile for the attribute *smiling*.

a total of 350+ distinct word suggestions⁴. In the end, we select the 10 most frequently appearing words as our fine-grained relative attribute lexicon for shoes: *comfort*, *casual*, *simple*, *sporty*, *colorful*, *durable*, *supportive*, *bold*, *sleek*, and *open*.

Generative Model Training

We train our attribute-conditioned image generator using a Conditional Variational Auto-Encoder (CVAE) [31]. The model requires a vector of real-valued attribute strengths for each training image. We detail the setup process for each dataset below.

Fashion Images of Shoes We use a subset of 38,866 images from UT-Zap50K to train the generative shoe model. Using the meta-data once again, we select 40 attributes ranging from material types to toe styles (e.g. Material.Mesh, ToeStyle.Pointed, etc.) and assign binary pre-labels to them. In addition, we also use the 10 fine-grained relative attributes collected from our lexical study. We sample 500 supervision pairs for each attribute from the newly collected pairwise labels and train a linear SVM rankers using Rank-SVM [20]. We then project all 1,000 images (used to train the ranker) onto the learned ranker to obtain their real-valued ranking scores, which we use as their pre-labels. While our focus is on the 10 relative attributes, the inclusion of additional attributes aids in overall learning of the generative model. However, we do not use any of those meta-data attributes for fine-grained relative attribute training as they are mostly binary in nature.

Finally, using these pre-labels from all 50 attributes, we train a linear classifier for each attribute. We apply the classifier on all 38,866 images and use their decision values as the real-valued attribute strength needed to train the generative model.

⁴We used only the words from Design 1 as the two designs produced very similar word suggestions.

All of this is a workaround, similar to the one used in [31], in order to supply the generative model with real-valued attribute strengths on its training data. If labeled binary attribute data were available for training the linear classifiers from the onset, that would be equally good if not better.

Human Faces We use a subset of 11,154 images from LFW [41] to train the generative face model. Following [31], we use the 73 dimensional attribute strength provided in [42] to train the generative face model.

Synthetic Test Images

Table VI shows the per-attribute breakdown of our synthetic test images experiment. This corresponds to Table 5 in the main paper, where due to space limitations we summarized results over all attributes for the dataset.

Global Classifier

As noted in experiments, results for all methods were typically better using local learning as opposed to training global rankers with all available labeled data. For completeness, we show the comprehensive results here in Table VII and VIII. For Zap50K, our approach outperforms all global baselines by a minimum of 2%. For PFSmile, the global variant of our approach performs slightly better than our primary local model, perhaps because the real training and testing pairs are from different datasets.

One Word Challenge: Shoe Pairs

Complete each sentence using one word that describes subtle differences.

Instructions:

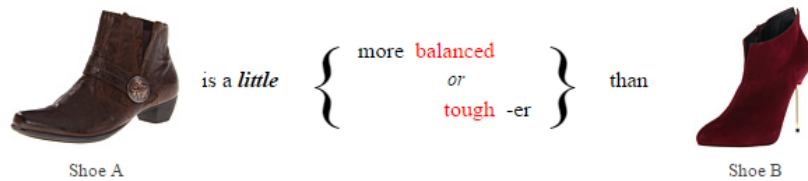
- The purpose is to identify SUBTLE differences between each pair of images. e.g. color is *too obvious*.
- Provide a brief elaboration of the word choice (max: 140 characters).
- Please answer ALL questions. We expect it will take you 1-2 mins.

Additional Notes:

- Fill each box with one word ONLY. Choose from EITHER forms: "more _____" or "_____ -er"
- The word "more" can be replaced with the word "less" if necessary. Specify during elaboration.
- Answers containing TWO WORDS or more will automatically be rejected.

Please *ACCEPT* the *HIT* first before starting. Thank you for doing this *HIT*!

Example



Elaborate: Shoe A has more padding.

Image Pair #1



Elaborate on your word choice.

Fig. 6: Screenshot of our lexical experiment on MTurk in Design 1.